

Influence of Electric Bicycle Usage on Biker Effort

On-road Monitoring Application in Lisbon, Portugal

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Abstract: Bicycle use in urban environments is an alternative mobility option, which enables people to travel longer, faster and with less effort than walking, with low environmental impacts. The use of electric bicycles (EB) has risen as another possibility to promote a more efficient transportation use. However, the quantification of the real impacts for the biker of shifting from conventional (CB) to EB is not yet quantified. This research work aims at estimating the impacts on physiological signals, namely, on heart rate, from using EB instead of CB, using a suitable methodology for on-road bio-signals data analysis. The on-road monitoring of 6 bikers, 2 routes and 3 bicycles in Lisbon presented a 57% average reduction in HR variation from using EB, since under high power demanding situations, the electric motor attenuates human effort. It was also possible to estimate the energy expenditure associated to the human effort that results from using the bicycles. For the CB the total energy spent reaches ≈ 70 Wh/km, while the EB presents ≈ 51 Wh/km of human energy (28% lower than the CB) and ≈ 9 Wh/km of electricity consumption, resulting in a total of ≈ 60 Wh/km. Consequently, the total energy per km is 14% lower in the EB compared to the CB.

1 INTRODUCTION

The transportation sector faces increasingly demanding energy consumption and emissions standards representing 33% of the final energy consumption, with the road transportation sector being responsible in 2011 for 82% of that energy consumption (EUROSTAT, 2013).

One alternative to reduce the impact of the transportation sector, particularly in urban environments, is to decrease the demand for energy intensive modes of transportation and by promoting alternatives that can provide a cheaper, less noisy and more sustainable alternative than a day-to-day car commute. Generally, three alternative transportation models can be identified: public transportation systems (bus, trains, subway systems and others), vehicle sharing schemes (such as cars or bicycles), and alternative transportation modes such as walking, private bicycles or others (Wang, 2011). From these different alternatives, the use of bicycles is one of the more advantageous as it allows the users to move at significant speeds for short distances (typical in urban environments), resulting in no emissions and having health benefits (Lindsay et al., 2011).

Using bicycles enables people to travel longer,

faster and with less effort than walking, while having a low impact on environment, thus making it an efficient transportation mode for urban mobility. As a result, the importance of cycling has been increasing worldwide (Freemark, 2010; Urban Audit). In many developing countries, namely in Asia, two-wheelers are a first affordable step towards individual mobility. In European and American cities, the deployment of city bike ways infrastructure has also been increasing, with bike sharing systems deployed having in average 200 km of bike lanes (Baptista, 2013).

Concerning the use of bicycles on urban environments, a growing number of cities have been trying to integrate them in the daily mobility of their citizens, which for some countries has resulted in a significant share of trips being done using a bicycle, such as the Netherlands (26%), Denmark (18%) and Germany (10%) (Buehler and Pucher, 2012). In the city of Amsterdam, 38% of all trips in 2008 were made using a bicycle, with 50% of Amsterdam's residents riding a bike daily and 85% riding it at least once a week (Gardner, 2010).

While the use of conventional bicycles in an urban context has been promoted with significant success in several cities, namely Paris and London with 25000 and 8000 deployed bicycles respectively

(Barclays Cycle Hire, 2012); (Lathia et al., 2012); (Vélib, 2012), they still have several drawbacks that hinder their widespread use. Some of the main problems identified by people when using conventional bicycles for urban transportation include the difficulty to travel very long distances and over hills, the possibility of arriving at a destination, such as work, sweaty or tired (Dill and Rose, 2012), being exposed to extreme cold or hot climates, among others. Even some cities with difficult topographies, such as Lisbon, have also begun promoting the use of bicycles through the creation of bike lanes and studying the possibility of having bike sharing schemes (Galp Energia, 2012); (Martinez et al., 2012).

Several of these issues can also be overcome through the use of electric bicycles (Dill and Rose, 2012). Generally, it is expected that the use of electric bicycles can help reduce the effort required for performing trips as well as reduce travel time, though at a higher cost due to the electric system and the energy used.

One of the main applications of electric bicycles is in bike sharing systems, with several systems being deployed worldwide. The Callabike system in Aachen, Germany, has recently deployed a fully electric bike sharing system with 15 electric bicycles (Callabike, 2012). The city of Kitakyushu in Japan also presents a full electric system with 116 bikes (The Bike-sharing Blog, 2011). Cities such as St. Etienne and Poitiers in France present mixed conventional and electric bike sharing systems with a 15% and 26% ratio between electric and conventional bicycles respectively (Cap'Vélo, 2012); (VéliVert, 2012).

Both conventional and electric bicycles are starting to be seen as a real option under urban environments, however, the real impacts on human efforts have not yet been accounted under real operation. Also, despite the high expectations for electric bicycles, very few studies have tried to understand the real world benefits of such bicycles in an urban environment.

Regarding environmental impacts, for instance, in China the estimation of environmental impacts comparing electric bicycles with other means of transport (bus) (Cherry et al., 2009) remarks that electric bikes, in a life cycle perspective which includes the well-to-tank stage, have higher emissions of SO₂ (due to burning coal for electricity production) compared to a bus, however the emissions of other pollutants are lower in electric bike. As result, pollutant emissions are strongly related to the energy mix. The emissions associated

with the production process of batteries, recycling and "dump" are also a concern.

Considering the adoption of electric bicycles, the benefits of using electrical technologies are not unanimous (Cherry and Cervero, 2007). The potential environmental impacts, interference with traffic and safety issues, as well as the potential conflict between users of electric bikes and conventional is a concern, since the speed differences during cycling can pose a problem (Dill and Rose, 2012).

Therefore, in terms of conventional and electric bicycle usage comparison (Baptista et al., 2013b), a 16% increase in average speed was verified in electric bicycle over that achieved with the conventional bicycle. Different usage strategies of the bicycle were also identified: the first strategy of using the electric bike is to use a high level of electric assist on positive slopes (uphill conditions), lowering the electric assistance levels for neutral and negative slopes; in the second strategy, the rider uses more electric assist on the positive slopes, assistance decreases in negative slopes, and reaching the lowest values in the plain areas; and the third strategy is to always use a high level of service regardless of the slope.

The biker driving dynamics represented by the speed and acceleration, combined with road topography, reflects in a power demand that must be overcome either by the biker (in a CB) or by the biker and/or the electric motor (in an EB). The quantification of human effort during cycling can be addressed (Parkin, 2011), using a formula that includes variables such as speed, acceleration, mechanical efficiency of the bicycle, among others. The author states that the slope of the road influences the energy spent by the cyclist, as well as the number of stops. Just stopping at an intersection can lead to an increase of 10% in energy consumption.

An important issue is the quantification of the amount of effort or energy that the rider expends to complete a specific route. More importantly, whether an electric bike will actually decrease the effort or energy expended by the rider when compared with a conventional bicycle is also an issue. There is little work developed in this field and it does not reflect real world use of conventional and electric bicycles. Therefore, a method to estimate human energy expenditure (EE) must be addressed. This method must include physiological data that can be related with energy expenditure and an analysis that could use on-road, real-world operation of electric and conventional bicycles.

A strategy for quantifying the human effort is the comparison between ventilation and heart rate as an indicator of oxygen consumption during exercise with different intensities (Gastinger et al., 2010). By monitor individuals performing different tasks (such as walking, walking carrying a certain load and intermittent work), the authors concluded that the most appropriate methodology is the heart rate to determine the oxygen consumption. Another possibility is a calorimeter indirect way versus heart rate monitoring to evaluate energy consumption (Yu et al., 2012). The authors state that for determining energy consumption, in tasks of day-to-day, the two methods have very similar values, 8.6 kcal/day. However, the authors argue that the method of using the heart rate, to determine the energy consumed in the daily tasks, still needs improvements.

Accurate estimate of energy consumption through the heart rate without individual calibration laboratory can be performed (Pulkkinen et al., 2005). The authors argue that the methodology RR_{REST} where individual calibration of heart rate is not necessary, provides an accurate and practical way to estimate the power consumption.

The comparison of two techniques to estimate the energy consumed, obtained by monitoring the heart rate, and obtained by a portable electromagnetic coil (Gastinger et al., 2012) allows concluding that the determination of the energy consumed using electromagnetic coil portable system is more accurate than using only the heart rate. The authors also report that would be interesting to use together, heart rate and ventilation on the determination of the energy consumed.

Several other techniques to determine the energy consumed are available or being developed, with particular reference to Doubly Labelled Water (DLW) (Ainslie et al., 2003). In this study, the authors argue that the methods used to determine the power consumption depends on factors such as the number of individuals monitored and the monitoring period. The authors suggest that studies with few participants and short analysis periods, should use the method of indirect calorimeter to obtain best results. However, for longer periods, around 3 to 4 days, it is preferable to use the method of DLW.

Although there are several techniques available, the prediction of the energy consumed during submaximal exercises could be done using heart rate readings (Keytel et al., 2005). Through tests conducted at 115 individuals in ergonomic bikes and treadmills race, the authors established an equation to determine the energy consumed by an individual during exercise. This equation includes the

following variables: heart rate, age, sex and weight. The authors claim that it is possible to determine with good precision, the energy consumed using only heart rate, age, sex and weight, and without the need for individual calibration.

As can be seen, most of the techniques to estimate human energy expenditure were performed under controlled conditions – unlike the study presented, but present solutions and correlations that include signals such as heart rate that can be collected while the bicycles are used.

According to this framework, the objectives of this research work were to develop a methodology based on physiological data collection under regular bicycle operation. The goal was to evaluate the application of conventional and electric bicycles for urban mobility focusing on typical hilly routes of Lisbon, quantifying their correspondent effect on human energy expenditure.

2 METHODOLOGY

2.1 On-road Monitoring

The evaluation of electric and conventional bicycles was done through the monitoring of trips performed by 6 male different bikers (within the same age range and physical characteristics), with each biker travelling the same urban tour with both bicycles. The bikers used the electric bicycle first and the conventional bicycle after, with a minimum resting period of 1 hour in-between.

The bicycles used by all bikers were the same, in order to enable a fairer evaluation, although two models of electric bicycles were evaluated. The specifications of the three bicycles used are the following:

- Conventional bicycle (CB) (Orbita Aluminio): weight of 15 kg, 21 gears;
- Electric bicycle (EB1) (QWIC Trend2): power assist electric bicycle with six levels of assistance, 25.7 kg, 7 mechanical gears and a detachable Li-ion battery with a 360 Wh capacity, provided by Prio.Energy (Prio Energy, 2012); and
- Electric bicycle (EB2) (Ekoway L1): power assist/power on demand electric bicycle with 23 kg, 6 mechanical gears and a detachable Li-ion battery with a 360 Wh capacity, provided by EcoCritério (Eco-critério, 2013).

Each trip was monitored during the ride using a monitoring laboratory designed to assess energy and

environmental impacts associated to non-motorized modes, MoveLab. This laboratory was assembled by the DTEA - Transport, Energy and Environment research group of IDMEC – IST and corresponds to a backpack weighting 12 kg that the user (pedestrian or biker) carries, as shown in Figure 1.



Figure 1: MoveLab components and experimental apparatus used for the real time monitoring (a), electric bicycle (b) and conventional bicycle (c).

MoveLab is equipped with a GPS to record the dynamic profile of the trip (including location, altitude and speed), voltage and current probes to assess the levels of electric assistance, and biometric sensors (recording heart rate and breathing intensity). All these equipment was carried by the rider in the backpack. When asked to carry the MoveLab backpack, the bikers saw no inconvenience since in their daily routines they already carry backpacks weighting around 5 to 8 kg.

All the MoveLab equipment is connected to a laptop running a purposely developed software in LabView to synchronize and record the data at 1 Hz, throughout the trip. The technical description of the equipment used is presented in Table 1.

Adding to the MoveLab, it was used bioPLUX Research hardware and software acquiring physiological data simultaneously. In order to synchronize the two sources of data (LabView and

bioPLUX Research), a force sensor was adapted to the numeric pad. This way, when the biker pressed Enter, this signal was recorded either in LabView and Plux software. Since the bio-signals require a high frequency data logging, a minimum of 200 samples per second were collected while the biker was riding. Due to the different temporal resolution physiologic data was post processed into a second by second time basis.

Table 1: Technical description of the equipment in MoveLab.

Monitoring equipment	Data acquired	Temporal resolution of data (Hz)
GPS (Garmin GPS map 76CSx)	Speed (km/h), altitude (m), location	1
Voltage and current probes (Fluke i1010)	Voltage, current	1
bioPLUX Research	Heart rate, Breathing rate	200

2.2 Data Collection and Processing

The GPS allows collecting speed, location and also altitude information via an integrated barometric altimeter. The altimeter was adequately installed inside the backpack, avoiding pressure fluctuations due to movement that could affect the readings. An external antenna was used to avoid GPS signal losses. Voltage probes were installed directly in the bicycle battery terminals, while current measurements were done on the circuit that connects the battery to the electric motor. The signals provided by the probes were collected by a National Instruments DAQ board installed also on the backpack. For battery voltage signal a voltage divider circuit was placed before the DAQ board to account for the 0-10 V limit of the acquisition device. Both GPS and battery data were collected in a PC using a program developed in LabView by the authors to integrate the different communication protocols (serial port and NMEA protocol for GPS and analog data via USB port for the voltage and current collected in the DAQ board) that allows to synchronize the data, capturing all the equipment readings in a 1 Hz basis. A solid-state disk PC was used to avoid data loss while in motion.

The bioPLUX Research tool was used to collect heart rate and breathing rate. This information was collected at 200 Hz using PLUX software. Post processing of data included the conversion of the data to 1 Hz basis. It should be noticed that breathing rate measured is very sensible to vibration under regular bicycle operation, therefore it was decided not to use this data.

GPS readings of speed were used to post process distance travelled, acceleration and road grade. Altitude and distance were used to determine the trip road grade using an algorithm that, for each point of the trip, finds the points 50 m before and after and uses this information to establish a second order polynomial fit based on three points of distance and altitude. The derivative of the polynomial fit in the studied point allows determining road grade, which is presented in rad.

Battery data was used to determine, at each point of the trip, the power provided by battery to the electric motor, according to the biker demands, and integrate this data along the trip to find the cumulative energy spent on the predefined tour.

With the data collected it is possible to understand and quantify how riders changed their use profile (in terms of speed and acceleration), changing from a conventional bicycle to an electric one. Also, the physiological impacts on the adoption of an electric bicycle versus the conventional were addressed using the physiological data, which also is intended to provide an estimate of the human energy expenditure.

2.3 Monitored Tours

To compare the use of conventional and electric bicycles, round-trip tours of approximately 8.5 km and 5.7 km were performed by each biker, in Lisbon, with both bicycles. One of the tours consisted on going from Instituto Superior Técnico (IST) main campus to downtown Lisbon and back, passing through the top of the Parque Eduardo VII and Avenida da Liberdade on both ways. With this tour, the bikers crossed different parts of the city of Lisbon including traffic intensive avenues, side roads with very little traffic and a street with a bike lane. The other tour was carried in the EXPO 98 area, simulating a journey in a leisure place with low traffic conditions. In terms of topography, the tours had significant slopes, as summarized in Table 2.

Table 2: Selected routes.

Route	Distance (km)	Average positive slope (rad)	Average negative slope (rad)
R1	8.54	0.037	-0.029
R2	5.66	0.020	-0.017

2.4 Methodology for Data Analysis

The analysis used in this work is based on Vehicle Specific Power (VSP) to estimate the power demand by vehicles, which combines speed (v), acceleration

(a) and road grade (θ). This methodology allows comparing different technologies under similar power requirements. It is traditionally used on light-duty vehicles (Jiménez-Palacios, 1999) and its generic definition, which includes the forces applied to a moving body, is presented in Equation 1. The coefficients of the equation are adjusted according to the typology of vehicle monitored (Baptista et al., 2013a). In this case, the coefficients used, adapted to typical utility bicycles based on literature values (Wilson, 2004), are presented in Table 3, obtaining the bicycle specific power (BSP).

$$VSP = \frac{d}{dt}(E_{Kinetic} + E_{Potential}) + F_{Rolling} \cdot v + F_{Aerodynamic} \cdot v = (1)$$

$$v \cdot [a \cdot (1 + \varepsilon_i) + g \cdot \sin(\theta) + C_{Roll}] + C_{Aero} \cdot v^3$$

Table 3: Coefficient values for the variables included in BSP.

Variables	Values
ε	0.01
g (m/s ²)	9.81
C_r	0.008
C_d	1.2
A (m ²)	0.5
$m_{bicycle}$ (kg)	18
m_{biker} (kg)	70
ρ_a (kg/m ³)	1.2

Using the respective coefficients, the BSP, in W/kg) is defined by Equation 2:

$$BSP = v \cdot [1.01 \cdot a + 9.81 \cdot \sin(\theta) + 0.008] + 0.0041 \cdot v^3 \quad (2)$$

Similarly to the VSP methodology, the BSP is also divided in modes that cover the full spectrum of the bicycle operation, according to the following formulation: group points with similar BSP values (in W/kg); each BSP mode must include more than 1% of the total trip time, providing representativeness for each mode; and the number of modes is such that the total trip time is not concentrated in a limited number of points.

Table 4 presents the modes (or bins) used in this work and the respective range of power per mass.

Table 4: Binning method for BSP.

BSP mode	Definition	BSP mode	Definition
<-4	BSP<-1	1	0≤BSP<1
-4	-4≤BSP<-3	2	1≤BSP<2
-3	-3≤BSP<-2	3	2≤BSP<3
-2	-2≤BSP<-1	4	3≤BSP<4
-1	-1≤BSP<0	>4	BSP>4
0	BSP=0		

The percentage of time spent in each BSP mode for the conventional and electric bicycles is

presented in Figure 2 and Figure 3. For negative modes, the driving profile is very similar for both bicycles. However, on positive BSP modes, the electric bicycle present a higher share of time spent in high BSP modes (higher power demands). This is due to the electric assistance, which allows traveling at high speeds on higher slopes and combinations of higher speeds and acceleration, etc.

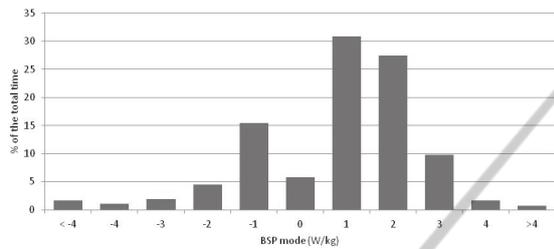


Figure 2: Time distribution (%) per BSP mode for conventional bicycle.

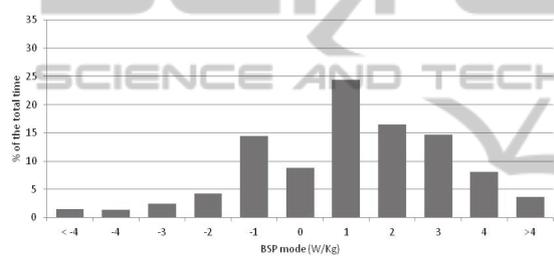


Figure 3: Time distribution (%) per BSP mode for the two electric bicycles.

Figure 4 presents the energy rate spent at each BSP mode, on average, for the electric bicycles studied, using the 1 Hz data from voltage and current provided by the battery, measured under on-road conditions. As expected, the energy rate increases with BSP mode, showing the dominance of electric assist on these modes.

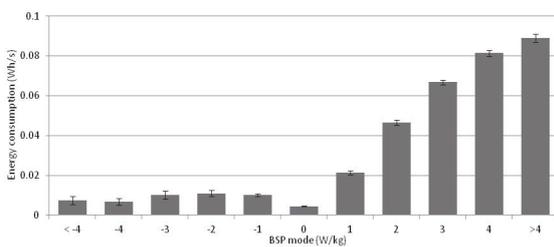


Figure 4: Electricity consumption for the electric bicycles as a function of BSP.

Although the data presented so far allows taking conclusions about usage patterns of biker in EB and CB, in both electric and conventional bicycles it is necessary to determine the physiological impacts of

each technology and the respective human energy expenditure to address the total energy impacts. The Results section focus on the methodology developed to assess this crucial part of the study.

3 RESULTS

Using the monitored heart rate data, the objective was to correlate trip dynamic variables (traduced by BSP) with HR variations. Hence, since BSP aggregates trip information of speed, acceleration and slope, its influence on heart rate was analyzed. Additionally, since HR differ from person to person, this analysis was done considering its derivate, $\left(\frac{\Delta HR}{\Delta t}\right)$, and not its absolute value. Also, since HR is an indirect unit of energy (as verified in the Introduction), $\left(\frac{\Delta HR}{\Delta t}\right)$ traduces the variation of Energy in a period of time, hence a measure of Power.

Due to the existence of some noise in the HR signal due to movement and vibration, the HR and BSP second by second data was aggregated in a minute by minute basis. In total, over 8 hour of data was collected.

Figure 5 presents a clear relation between BSP and $\left(\frac{\Delta HR}{\Delta t}\right)$. For mode 0, that corresponds to the biker stopped, a reduction in $\left(\frac{\Delta HR}{\Delta t}\right)$ is observed, which means that the biker reduced his HR in this condition, compared with the previous riding condition (thus $\left(\frac{\Delta HR}{\Delta t}\right) < 0$). For positive BSP modes, which require more power from the biker, positive variations in HR are observed due to the increased human effort. As a result, for increasing BSP modes, increasing positive variation in $\left(\frac{\Delta HR}{\Delta t}\right)$ are observed. BSP mode >4 has few riding data points, which justifies its divergence. For negative BSP modes, which usually correspond to braking or descent situation, reductions in HR/s are observed.

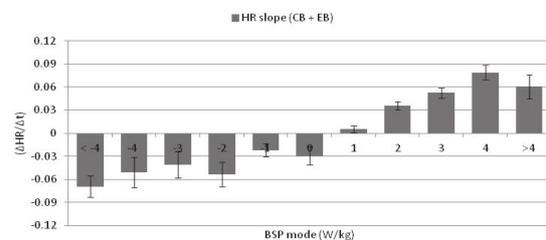


Figure 5: Influence of BSP in $\left(\frac{\Delta HR}{\Delta t}\right)$ for the total data collected.

The collected data was also disaggregated according to conventional and electric bicycle. Figure 6 presents the $\left(\frac{\Delta HR}{\Delta t}\right)$ average results according to the usage of conventional or electric bicycle. Over 4 hours of data are represented both for electric and conventional bicycles (considering the average of two electric and conventional bicycles that were monitored). The variations in HR/s are lower for the electric bicycle. That is mainly visible in positive BSP modes, where higher power demand is observed. For the electric bicycle, having the electric motor assistance, helps reducing the human effort and, consequently, variations in HR/s are lower. For negative BSP modes, that difference is not so visible, with both bicycles leading to reductions in HR. It should be noticed that for the highest BSP mode, the trend is not followed due to the lack of points to fully characterize those conditions.

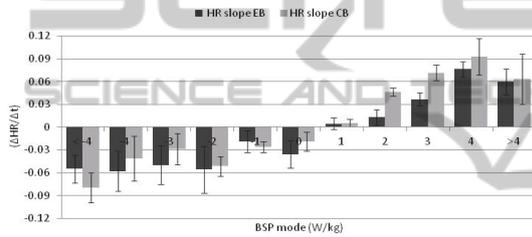


Figure 6: Influence of BSP in $(\Delta HR/\Delta t)$ for conventional (gray) and electric bicycles (black).

In order to obtain an average HR variation at the end of the trip, the temporal distribution of BSP was multiplied by the HR variations. Table 5 presents the average $\sum(\Delta HR)$ for each type of bicycle. The electric bicycle leads to lower values compared to the conventional one, with an average 57% reduction.

Table 5: $\sum(\Delta HR)$ for CB and EB.

Bicycle	$\sum(\Delta HR)$
EB	0.59
CB	1.37

The next step was to analyze the human energy expenditure (EE) associated to each trip. This corresponds to the energy spent by the biker to drive the bicycle. According to the literature review (Ainslie et al., 2003); (Gastinger et al., 2012); (Keytel et al., 2005) this corresponds to an accurate approximation to account with the energy the body burns during physical activity. The estimation of EE can be performed using the equations presented in Table 6.

Table 6: Quantification of EE from HR.

Source	EE
(Keytel et al., 2005)	$EE = \text{gender} \times (-55.0969 + 0.6309 \times HR + 0.1988 \times \text{weight} + 0.2017 \times \text{age}) + (1 - \text{gender}) \times (-20.4022 + 0.4472 \times HR - 0.1263 \times \text{weight} + 0.074 \times \text{age})$ <p>EE in kJ/min; HR in BPM; gender=1 for man and 2 for woman. In this study, all biker were male, with an average age of 28 and average weight of 70 kg.</p>
(Gastinger et al., 2012)	$EE = 0.103 \times HR - 4.795$ <p>EE in kcal/min; HR in BPM</p>
(Ainslie et al., 2003)	$EE = 0.0056 \times HR^2 - 0.6908 \times HR + 26.532$ <p>EE in kJ/min; HR in BPM</p>
Average equation	$EE = (9 \times 10^{-6}) \times HR^2 + 0.0006 \times HR - 0.0449$

The 3 equations presented can be represented simultaneously to obtain Figure 7 and an average equation was obtained (Table 6) that was used for the purpose of this study.

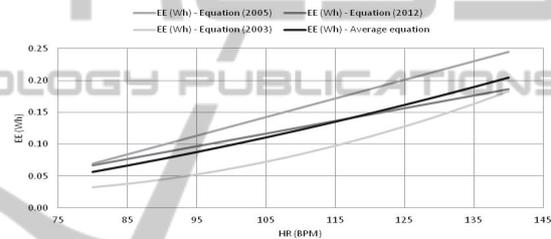


Figure 7: EE as a function of HR.

Using the 8 hours of physiologic data (divided in 4 hours for CB and the remaining for EB) and recurring to the obtained average equation (Table 6), the EE value was estimated to each second of the trip. The next logical step was to group points with similar BSP conditions, to obtain a representative EE value associated to each BSP mode. This data is presented in Figure 8, with the gray bars representing CB and the black bars representing the EB.

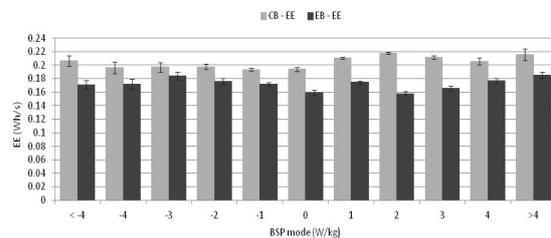


Figure 8: EE per BSP mode for CB and EB.

Figure 8 presents the results of multiplying the EE profiles (in Wh/s) by each trip BSP time distribution, for EB and CB. This way, the EE (in Wh) for each BSP mode is obtained. Adding the EE at each BSP

mode and dividing by the trip distance, an estimate of the human energy expenditure per kilometer (Wh/km) is assigned for each trip and technology used (conventional or electric).

In order to obtain the total energy consumption (human and electric), an approach similar to the one described previously was used for estimating electric use, according to the consumption profile distribution from Figure 4, instead of Figure 8.

Figure 9 presents an estimate of the total energy per kilometer (human plus electric in electric bicycle and human only in conventional bicycle). For the conventional bicycle the total energy is around 69.8 Wh/km, while the electric bicycle presents 50.6 Wh/km of human energy (less 27.5% compared with conventional bicycle) and 9.2 Wh/km of electric consumption, resulting in a total of 59.8 Wh/km. Therefore, the total energy per kilometer is 14.3% lower in the electric bicycle than in the conventional.

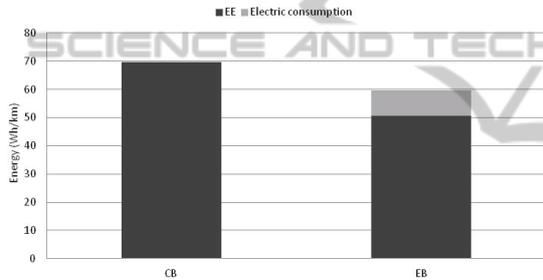


Figure 9: Total energy expenditure for CB and EB.

With the data collected, it was not possible to effectively estimate the efficiency of the electric motor and the human body while cycling. However, it is possible to obtain a set of acceptable values for those efficiencies. Therefore, it was assumed that to travel the distance of one kilometer it is necessary the same energy, independently of using the electric and conventional bicycle (Eq. 3).

$$E_{\text{req_CB}} = (\epsilon_H \times EE_{\text{CB}})$$

$$E_{\text{req_EB}} = (\epsilon_H \times EE_{\text{EB}}) + (\epsilon_M \times \text{Electricity consumption}) \quad (3)$$

$$E_{\text{req_CB}} = E_{\text{req_EB}}$$

Where $E_{\text{req_CB}}$ is the required energy for CB; $E_{\text{req_EB}}$ is the required energy for EB; ϵ_H – is the human body efficiency; ϵ_M is electric motor efficiency; EE_{CB} is the EE for CB; and EE_{EB} is the EE for EB. Using to Eq 3 and assuming a range of typical efficiency values for an electric motor, between 60 to 95%, the range of human efficiency can be estimated, as presented in Figure 10. As a result, while cycling, the efficiency of human body, theoretically, ranges from 30% to 45%.

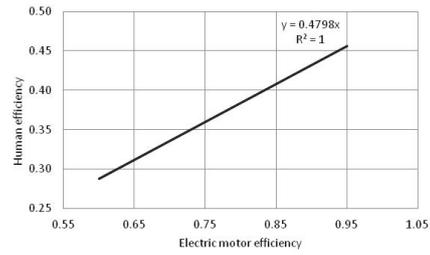


Figure 10: Human efficiency versus electric motor efficiency.

4 CONCLUSIONS

This research work addressed the use of conventional and electric bicycles in real world conditions, in order to estimate its impacts on physiological signals, in more detail, in heart rate and human energy expenditure. For this purpose a methodology to express the power required to overcome a drive cycle was adapted for bicycles, resulting in the BSP methodology. The application of this methodology used as basis data from the monitoring of 6 bikers using both CB and EB, over 114 km in the city of Lisbon, Portugal, showing that EB allow reaching higher BSP modes. However, the developed methodology is not city or route specific and can be applied elsewhere.

The impact on heart rate from shifting from conventional bicycle usage to electric bicycle usage was estimated. An average 57% reduction in HR variations was found for the use of EB in typical trips since, in high BSP modes that represent power demanding situation, the electric motor comes in action, avoiding human effort.

Moreover, a methodology was developed to quantify the energy expenditure, based on heart rate data measured under regular bicycle operation, associated to the human effort that results from using the bicycles. For the conventional bicycle the total human energy expenditure reaches ≈ 70 Wh/km, while the electric bicycle presents ≈ 51 Wh/km of human energy (27.5% lower than the conventional bicycle) and ≈ 9 Wh/km of electric consumption, resulting in a total of ≈ 60 Wh/km. Consequently, the total energy per kilometer is 14.3% lower in the electric bicycle compared to the conventional.

In all, an innovative method of quantifying the benefits for the biker of using electric bicycles was developed, resulting in significant reduction in heart rate variations, as well as, considerable energy efficiency improvements. Using all the modal information from Figures 4 and 8 regarding electric

and human energy rates, combined with BSP modal distribution for any route (as is presented in Figures 2 and 3), this methodology allows estimating the total energy expenditure (human and electric), electric autonomy, as well as HR variations, according to the trip profile. As a result, this methodology can be applied to evaluate the potential use of EB in specific situation, namely bike-sharing routes, providing significant support to bike-sharing systems design and deployment.

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